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A ROBUST TECHNIQUES OF ENHANCEMENT AND SEGMENTATION BLOOD VESSELS IN RETINAL IMAGE USING DEEP LEARNING

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ABSTRACT

The retina is the most important part of the eye. Early detection of retinal disease can be done through the passage of the blood vessels of the retina. Enhancement of the quality of retinal images that have both noise and noise is the first step in image processing to help improve the accuracy of the results for image segmentation and extraction. Images store a lot of information, but often there is a decrease in quality or image defects. So that images that have experienced interference or noise are easily interpreted, then the image can be manipulated into other images of better quality using image processing techniques or methods. The neural network-based method that is currently popular is deep learning. The segmentation process is currently a widely used method of deep learning that has grown rapidly used in various studies. One of the popular methods is Convolutional Neural Network (CNN). CNN can handle large-dimensional data such as images because the input to CNN is in the form of a matrix. Since the findings of retinal blood vessel segmentation are often inaccurate and there is always noise, this study will look at how to segment retinal images in blood vessels using CNN U-Net and LadderNet methods. Proper segmentation of retinal blood vessels can be the first step to detecting a disease. Segmentation and analysis of retinal blood vessels can assist medical personnel in detecting the severity of a disease. The stages of image enhancement used are Histogram Equalization and Clahe. Segmentation of blood vessels is done using CNN U-Net and LadderNet Methods. The results of the application of the enhancement and segmentation using the U-Net and LadderNet methods on training and on testing data were tested on the DRIVE dataset. The results of measurement of accuracy, specificity, sensitivity and F1 Score of blood vessel segmentation using the U-Net CNN method were 95.46%, 98.56%, 74.20%, and 80.63%, respectively. While the results of the CNN LadderNet method were 95.47%, 98.42%, 75.19%, and 80.86%, respectively. Based on the results of blood vessel segmentation from two proposed methods, the result of the CNN LaddetNet method is greater than the CNN U-Net method in accuracy, sensitivity, and F1 Score. The proposed approach will be further developed in the future, with the aim of increasing the value of the blood vessel segmentation process evaluation outcomes.

Keywords: Blood vessels; Clahe; histogram equalization; LadderNet; segmentation; U-net.

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INTRODUCTION

The retina is the thinnest portion of the cell within the eye, and it is made up of two types of cells: rods and cones. Doctors can diagnose retinal disease more easily with the aid of photographs, so it can be handled right away. The image is processed using a procedure to achieve the desired results of image processing. The optical disk, hemorrhage, exudates, and blood vessels are the four components of the retinal picture map.

The separation of objects into the background and foreground is known as image segmentation, and the image can then be used as input to the next step. Full segmentation and partial segmentation are the two forms of image segmentation. Full segmentation separates the image object from the background and assigns a label to each segment, while partial segmentation separates the image object from the background only.

Blood vessel segmentation is a technique for detecting eye problems. To diagnose eye conditions, ophthalmologists use one of the two methods: an ophthalmoscope instrument or a fundus camera.

Many other researchers have studied blood vessel segmentation, including Ref. 1 using morphological and Otsu's thresholding methods. The disadvantage of this approach is that it requires more work to enhance the accuracy of retinal vascular assessment such as developing a noise reduction technique to eliminate lesions and adapting the proposed method to other forms of image databases. The accuracy of this method is also small when compared to other published works.

Reference 2 used fuzzy c-means clustering and level set method. Visual comparisons in this method are still considered merely subjective. Reference 3 used particle swarm optimization (PSO) algorithm method. This approach requires the introduction of vessel morphology to improve vessel segmentation and obtain better performance. Reference 4 used glcm and fuzzy c-means. Detection of large and thin vessels on retinal images still needs more robust and efficient further research. Reference 5 used local adaptive thresholding technique based on glcm-energy information method. The disadvantage of this approach is that it necessitates more research into soft computing and, in particular, the use of heuristics to detect more thin vessels.

Reference 6 used mathematical morphology methods and pre-processing phase with k-means clustering. This method has a lower false positive-rate. Reference 7 used the selective binary and Gaussian filtering regularized level set (SBGFRLS) and the local binary fitting (LBF) methods. The weakness of this method is that the SBGFRLS and LBF models do not work well in real image segmentation.

Reference 8 used Otsu algorithm and tensor coloring methods. This approach requires the use of a hyperparameter optimization technique to optimize all the parameters of the proposed retinal vessel segmentation algorithm. Reference 9 used support vector machine (SVM) classifier method. This method will be difficult to segment because of the presence of vessels and intense interaction with drusen.

Reference 10 used contrast limited adaptive histogram equalization (CLAHE) and modified iterative self-organizing data analysis technique (MISODATA) methods. This approach does not understand the background of retinal thin vessels and frequent loss of vascular connectivity. Reference 11 used contrast limited adaptive histogram equalization (CLAHE) and morphological filter methods. This method is so old that it must be compared with current methods to be effective in terms of judgment and reliability. Reference 12 used morphological operations, contrast limited adaptive histogram equalization (Clahe), Retinex approach. b-Cosfire and Frangi matched filters, and Adaboost classifier methods. The weakness of this method is that the visual comparison is still subjective.

Reference 13 used k-Means clustering and first-level classification used Naïve–Bayes classification algorithm and second-level classification used C4.5 enhanced with bagging techniques methods. This approach requires investigating the impact of the training image and refining the segmented image generated by the data mining process to produce a better performance measure. Reference 14 used line set-based feature, local intensity feature, and morphological gradient feature and SVM for train methods. This method takes a long time to perform a more accurate segmentation. Ensemble learning can help improve classifier performance. Reference 15 used multiscale analysis of the stationary wavelet transform using a multiscale fully convolutional neural network method. The disadvantage of this approach is that it needs further research into the use of deep learning in conjunction with domain knowledge.

Sometimes the retinal blood vessel segmentation results are incorrect and there is still noise, so this study will discuss the process of segmenting retinal images in blood vessels using the Convolution Neural Network (CNN) U-Net and LadderNet methods.

The novelty of this research is a new segmentation technique that combines enhancement images, namely Histogram Equalization and CLAHE with Convolution

Neural Network (CNN) U-Net and LadderNet methods on retinal blood vessels. Measurement results of blood vessel segmentation are accuracy, sensitivity, specificity, and F1 score.

The most contributing result is that the segmentation technique using CNN Laddernet is superior to CNN U-Net in retinal vascular segmentation. The proposed approach will be further developed in the future, to increase the value of the blood vessel segmentation process evaluation outcomes.

MATERIALS AND METHOD

The proposed approach for processing retinal images is through five stages, namely retinal image input, histogram equalization, Clahe, blood vessel segmentation using CNN U-Net and LadderNet methods, and measurement performance.

Materials

Retinal dataset is widely available and can be accessed free of charge on the internet including the Digital Retinal Images for Vessel Extraction (DRIVE) datasets DRIVE provides retinal data that can be accessed and obtained on the website https://www.isi.uu.nl/Research/Databases/DRIVE/. This dataset is a publication of the Image Sciences Institute (ISI) of the University of Utrech. Observations of 400 diabetic patients produced 40 images of blood vessels in the retina which were divided into 20 training images known as ground truth and 20 test images. Of the 40 images consisting of 33 images that do not have Diabetic Retinopathy marks and 7 images show mild Diabetic Retinopathy marks. Retina image shows mild Diabetic Retinopathy in the DRIVE dataset.

DRIVE dataset image input must be High Dimension. The prepared dataset is first resized to 565×585 pixels with 96 dpi and 712 KB in size and the image type is converted to Tagged Image File (.tif) format.

The image is cut into 9,500 randomly selected patches of image with a size of 48×48 pixels. Each image piece was extracted from 20 training data images and 20 test data images to form a training data set and test data. Areas outside the FOV (Field of View) have also been considered for patch extraction.

One patch set consists of 190,000 patches obtained by randomly extracting from 20 training images with 9,500 patches each. The dataset is divided into two parts, 90% is used for training as many as 171,000 patches and 10% is used for testing as many as 19,000 patches.

Experiment of Preprocessing

Histogram equalization

Histogram equalization is a technique for enhancing image quality by using a histogram. The histogram of a picture pixel is a histogram that shows the distribution of an image's pixel intensity values. The Opencv function is used to perform cv2.equalizeHist() in the histogram equalization preprocessing programming.

CLAHE

Contrast Limited Adaptive Histogram Equalization is a technique for enhancing image quality (enhancement). The enhancement allows the use of CLAHE to enhance the quality of low-contrast images and minimize noise for a better picture.

CLAHE divides the entire image into sections of identical size and the contrast of each section is increased so that the histogram of the output image matches the histogram defined by the distribution parameters. The adjacent small sections are then held together using bilinear interpolation to eliminate artificially induced boundaries.

CLAHE is implemented in several stages. First, determine the neighborhood square block to estimate the histogram for the local block. Then generate a transformation function with an equalization histogram and do a gray level mapping for each pixel. Each time, the histogram can be updated without recalculating the histogram across all pixels in the new block. Lastly, move the center of the block to adjacent pixel positions and repeat the process.

Segmentation Using U-Net

In convolution neural networks, there are a variety of architectures, including the U-Net architecture, which was used in this analysis. The U-Net architecture is a U-shaped architecture. The architecture is symmetrical and consists of 2 parts, the contraction path, and the expensive path.

Each path contracting process will result in the formation of two convolutional layers. The number of image input channels in the first layer contracting path phase is 1. Due to the increasing depth of the image in the convolution phase, the activation function used by ReLU, and the 5×5 kernel size, the number of channels changes from 1 to 32. The maximum pooling indicated by the red arrow is performed.

In the third layer contracting path process, the number of channels changed from 64 to 128 using the ReLU activation function and 5×5 kernel size. The picture is enlarged to its original size using the unsampling method.

To get more accurate estimates, the first layer's expensive path phase pools images with the second layer contracting path to merge information from previous layers. Using the ReLU activation feature and a 5×5 kernel size, the number of channels was reduced from 128 to 64. The green arrow is used to perform the unsampling technique.

In the second layer expensive path process, pooling image is done with the first layer contracting path. Using the ReLU activation feature and a 5×5 kernel size, the number of channels was reduced from 64 to 32. The output map segmentation with 1×1 kernel size changes the number of channels 32 to 2.

Segmentation Using LadderNet

The LadderNet architecture also uses the U-Net architecture, which differs only during the training process. If on the U-Net architecture, the architecture just has to train it once. However, on LadderNet, the U-Net architecture is trained twice.

The number of image input channels in the first layer contracting path phase is 1. Due to the increasing depth of the image in the convolution phase, the activation function was used by ReLU, and the 5×5 kernel size, the number of channels changes from 1 to 32. The maximum pooling indicated by the red arrow is performed.

In the third layer contracting path process, the number of channels changed from 64 to 128 using the ReLU activation function and 5×5 kernel size. The picture is enlarged to its original size using the unsampling method, as shown by the green arrow.

To get more accurate estimates, the first layer's expensive path phase pools images were used with the second layer contracting path to merge information from previous layers. Using the ReLU activation feature and a 5×5 kernel size, the number of channels was reduced from 128 to 64. The green arrow is used to perform the unsampling technique.

In the second layer expensive path process, pooling image is done with the first layer contracting path. Using the ReLU activation feature and a 5×5 kernel size, the number of channels was reduced from 64 to 32. The number of image channels 32 is the output of the first training.

Then comes the second training session for the first input channel, which takes 32 minutes (taken from the first training). The training process is similar to the U-Net architecture in that it continues until the number of channels 2 is reached, which is the output map segmentation.

RESULT

Image Acquisition

The DRIVE dataset of 20 images is used for the train and 20 images for the test. The dimension size of the dataset is converted to 565×585 pixels with 96 dpi and a size of 712 KB and the type to Tagged Image File (.tif) format.

Preprocessing

The preprocessing stage is used to improve image quality before segmenting it (enhancement). The preprocessing stage aims to improve the accuracy of segmentation. The preprocessing steps used were Histogram Equalization and CLAHE.

In the first preprocessing stage, the histogram equalization method is used, and the opencv function is used to perform cv2.equalizeHist (). The result histogram of used histogram equalization method on retinal image is as shown in Fig. 1(b).

The picture is divided into "tiles", which are small blocks (tileSize is 8×8 by default in OpenCV). The histogram will then be equalized for each of these blocks. The resulting histogram of the used CLAHE method is shown in Fig. 1(c).

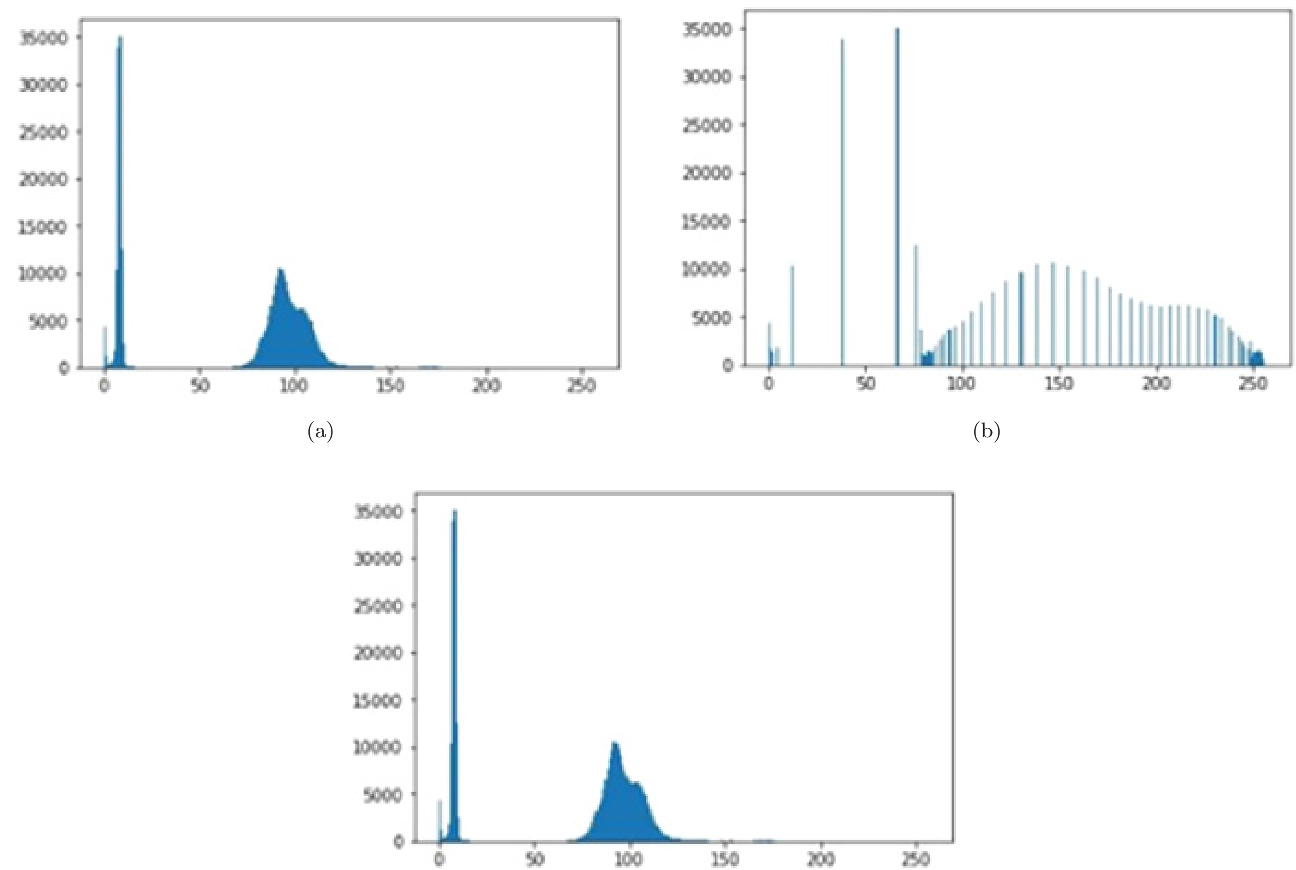
After the preprocessing stage which includes the Histogram Equalization and CLAHE methods, the result of pre-processing of the retinal image is shown in Table 1.

Segmentation Using U-Net and LadderNet

The CNN approach with U-Net architecture is used to segment blood vessels. The ReLU activation function and a 5×5 kernel size are used in the U-Net and the LadderNet architectures.

The result of training architectures U-Net and the LadderNet is segmentation blood vessels, as shown in Table 2.

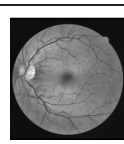
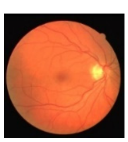
U-Net architecture training process is done by forming two layers of convolution, namely contracting path process and expensive path process. The first layer contracts path process, the number of image input channels is 1. The number of channels changes from 1 to 32 because convolution process will increase the depth of the image, the activation function used by ReLU and 5×5 kernel size. In the second layer contracting path process, the number of channels changes from 32 to 64 using ReLU activation function and 5×5 kernel size. In



(a) (b) (c)

Fig. 1 Histogram of retinal image: (a) Histogram original image, (b) histogram of histogram equalization and (c) histogram of CLAHE.

Table 1. The Result of Preprocessing Process Using Histogram Equalization and Clahe.

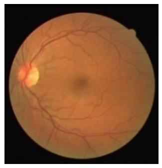
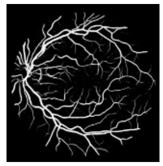
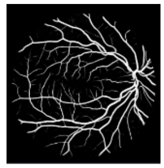
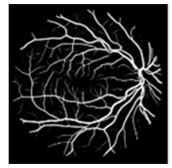
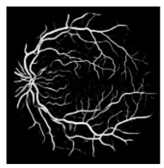
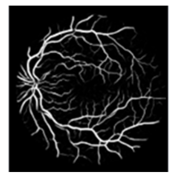
No	Original Image	Preprocessing
1.		
2.		
3.		

the third layer contracting path process, the number of channels changed from 64 to 128 using ReLU activation function and 5×5 kernel size. The upsampling technic is used to enlarge the image to original image.

In the first layer expensive path process, the image is combined with the corresponding image of the contract path to combine the information from the previous layer to get a more precise prediction. The number of channels changed from 128 to 64 using ReLU activation function and 5×5 kernel size. In the last layer expensive path process, the image is combined with the corresponding image of the first contract path. The number of channels changed from 64 to 32 using ReLU activation and 5×5 kernel size. The number of channels 32 changes to 2 which is the output map segmentation with 1×1 kernel size.

The blood vessel segmentation process uses the CNN method with LadderNet architecture. LadderNet architecture uses ReLU (Rectified Linear Unit) activation function and 5×5 kernel size. The LadderNet architecture actually uses the U-Net architecture, but it differs during the training process. If on U-Net architecture, the architecture is only trained once. But in LadderNet, U-Net architecture is trained twice. Each process constitutes two convolutional layers. In the first layer contracting path process, the number of image input

Table 2. The Result of Segmentation Blood Vessels using CNN U-Net and LadderNet Method.

No.	Original Image	Segmentation U-Net	Segmentation LadderNet
1.			
2.			
3.			

channels is 1. The number of channels changes from 1 to 32 because convolution process will increase the depth of the image, the activation function used by ReLU and 5×5 kernel size. In the second layer contracting path process, the number of channels changes from 32 to 64 using ReLU activation function and 5×5 kernel size. In the third layer contracting path process, the number of channels changes from 64 to 128 using ReLU activation function and 5×5 kernel size. The upsampling technic is used to enlarge the image to original image. In the first layer expensive path process, the image is combined with the corresponding image of the contract path to combine the information from the previous layer to get a more precise prediction. The number of channels is changed from 128 to 64 using ReLU activation function and 5×5 kernel size. In the last layer expensive path process, the image is combined with the corresponding image of the first contract path. The number of channels is changed from 64 to 32 using ReLU activation and 5×5 kernel size. The number of image channels 32 is output of the first training.

In the first layer contracting path process, the number of image input channels is 32 (taken from output the first training). In the second layer contracting path process, the number of channels changes from 32 to 64 using ReLU activation function and 5×5 kernel size. In the third layer contracting path process, the number of channels changed from 64 to 128 using ReLU activation function and 5×5 kernel size. The upsampling technic is used to enlarge the image to original image. In the first layer expensive path process, the image is combined with the corresponding image of the contract path to combine the information from the previous layer to get a more precise prediction. The number of channels is changed from 128 to 64 using ReLU activation function and 5×5 kernel size. In the last layer expensive path process, the image is combined with the corresponding image of the first contract path. The number of channels is changed from 64 to 32 using ReLU activation and 5×5 kernel size. The number of channels 32 changes to 2 which is the output map segmentation with 1×1 kernel size.

DISCUSSION

Performance Measurement Evaluation

The performance results, which are measured from segmentation blood vessels using CNN U-Net and LadderNet, are accuracy, specificity, sensitivity, and F1 score. Table 3 shows the parameter results achieved on the drive dataset.

Table 3. Parameter Result of Segmentation Blood Vessels.

Method	Accuracy	Specipicity	Sensitivity	F1 Score
CNN U-Net	95.46%	98.56%	74.20%	80.63%
CNN LadderNet	95.47%	98.42%	75.19%	80.86%

Based on the results of parameter measurement from CNN U-Net and CNN LadderNet methods in Table 3, accuracy in the CNN LadderNet method is greater 0.01% than the CNN U-Net method. Specificity in the CNN U-Net method is greater 0.14% than CNN LadderNet method. Sensitivity in CNN LadderNet method is greater than 0.99% than the CNN U-Net method. F1 Score in CNN Laddernet is greater 0.23% than CNN U-Net method. So from the comparison above, it can be concluded that the CNN Laddernet method is better than the CNN U-Net method.

Apart from getting the evaluation results above, this study also obtained the precision-recall curve and the ROC (Receiver Operating Characteristics) curve. The ROC curve displays a trade-off between the True Positive ratio and the False Positive ratio. The Precision-Recall Curve displays the trade-off between the True Positive ratio and the Positive Prediction value. Line X on the curve is the value of recall and line Y on the curve is the value of precision. AUC (area under the curve) is the area value under the precision-recall curve. The results of the precision-recall curve and the ROC curve are shown in Table 4.

Precision-recall curve from segmentation blood vessels using convolution neural network (CNN) U-Net with ReLU activation function and 5×5 kernel size, area under of the precision-recall curve (AUC) is 0.9068. Value of precision from parameter measurement is 0.8827 (88.27%) and value of recall from parameter measurement is 0.7420 (74.20%).

The precision-recall curve from segmentation blood vessels using CNN LadderNet with ReLU activation function and 5×5 kernel size, area under of the precision-recall curve (AUC) is 0.9056. Value of precision from parameter measurement is 0.8746 (87.46%) and value of recall from parameter measurement is 0.7519 (75.19%).

The ROC Curve is a curve showing the trade-off between True Positive rate and False Positive rate. Line X on the ROC Curve is the value of FPR (False Positive Rate(1–Specificity)) and line Y on the ROC Curve is value of TPR (True Positive Rate (Sensitivity)). AUC

Table 4. Precision-Recall and ROC Curves Results from the CNN U-Net and LadderNet Methods.

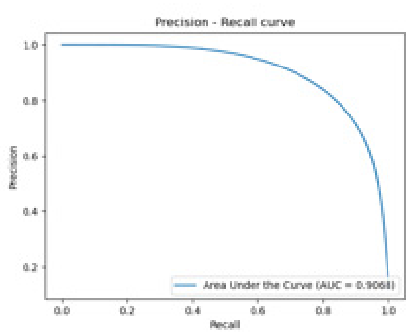
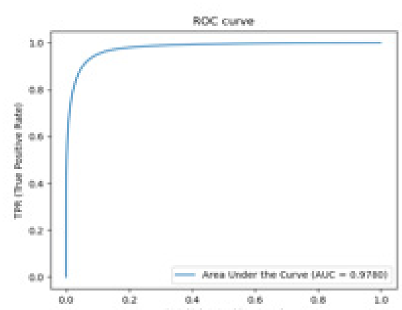
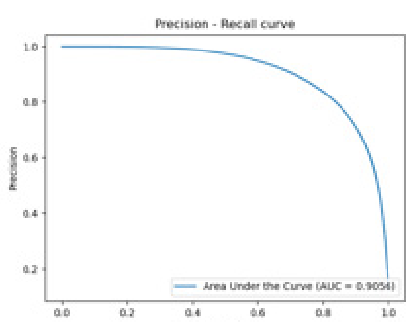
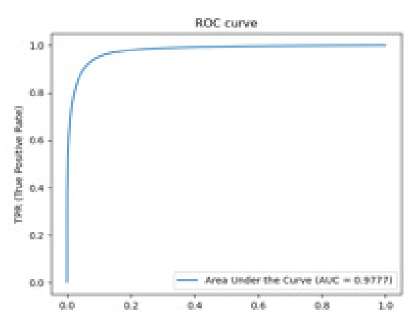
No.	CNN Methods	Curve Precission-Recall	Curve ROC
1.	U-Net	 AUC = 0.9068	 AUC = 0.9780
2.	LadderNet	 AUC = 0.9056	 AUC = 0.9777

Table 5. Performance Comparison of Proposed Method with Other Existing Method on DRIVE Dataset.

Method	Accuracy	Specificity	Sensitivity	F1 Score
CNN U-Net	95.46%	98.56%	74.20%	80.63%
CNN LadderNet	95.47%	98.42%	75.19%	80.86%
Morphological and Otsu's Thresholding[1]	92.06%	—	—	—
Fuzzy C-Means & Phase Congruence[4]	94.31%	—	—	—
Local Adaptive Thresholding Based On GLCM-Energy Information[5]	95.11%	—	—	—
The Local Binary Fitting (LBF)[7]	93.90%	96.80%	73.58%	—
Support Vector Machine (SVM)[14]	95.31%	—	—	—

(area under the curve) is the area value under the ROC curve.

The ROC curve from segmentation blood vessels using convolution neural network (CNN) U-Net with ReLU activation function and 5×5 kernel size, area under of the ROC curve (AUC) is 0.9780. The ROC curve using the CNN U-Net method is good because the point of the curve is close to 1.0.

The ROC curve from segmentation blood vessels using convolution neural network (CNN) LadderNet with ReLU activation function and 5×5 kernel size, area under of the ROC curve (AUC) is 0.9777. The ROC curve using the CNN LadderNet method is good because the point of the curve is close to 1.0.

Evaluation

Table 5 will show the comparison of the parameter measurement results from the proposed method with the methods of other existing using the DRIVE dataset:

According to Table 5, the proposed methods CNN U-Net and CNN LadderNet will outperform more than the five existing methods. Morphological and Otsu's Thresholding, Fuzzy C-Means & Phase Congruence, Local Adaptive Thresholding Technique Based On Information, The Local Binary Fitting (LBF), and SVM are some of the current methods.

CONCLUSION

Enhancement of preprocessing using Histogram Equalization and CLAHE methods can boost image quality, which is very useful during the blood vessel segmentation phase.

The results of measurement of accuracy, specificity, sensitivity and F1 Score of blood vessel segmentation using the U-Net CNN method were 95.46%, 98.56%, 74.20%, and 80.63%, respectively. While the results of the CNN LadderNet method were 95.47%, 98.42%, 75.19%, and 80.86%, respectively.

The results of the comparison of the two proposed methods obtained the accuracy of the CNN LadderNet method 0.01% higher than the CNN U-Net method. The specificity in the CNN U-Net method is 0.14% greater than the CNN LadderNet method. Sensitivity in the CNN LadderNet method is 0.99% greater than the CNN U-Net method. F1 Score in CNN Laddernet is 0.23% greater than CNN U-Net method. As a result of the comparison above, the CNN Laddernet approach is superior to the CNN U-Net method.

The proposed approach will be further developed in the future, to increase the value of the blood vessel segmentation process evaluation outcomes.

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